On the Automatic Design of a Representation for Grammar-based Genetic Programming

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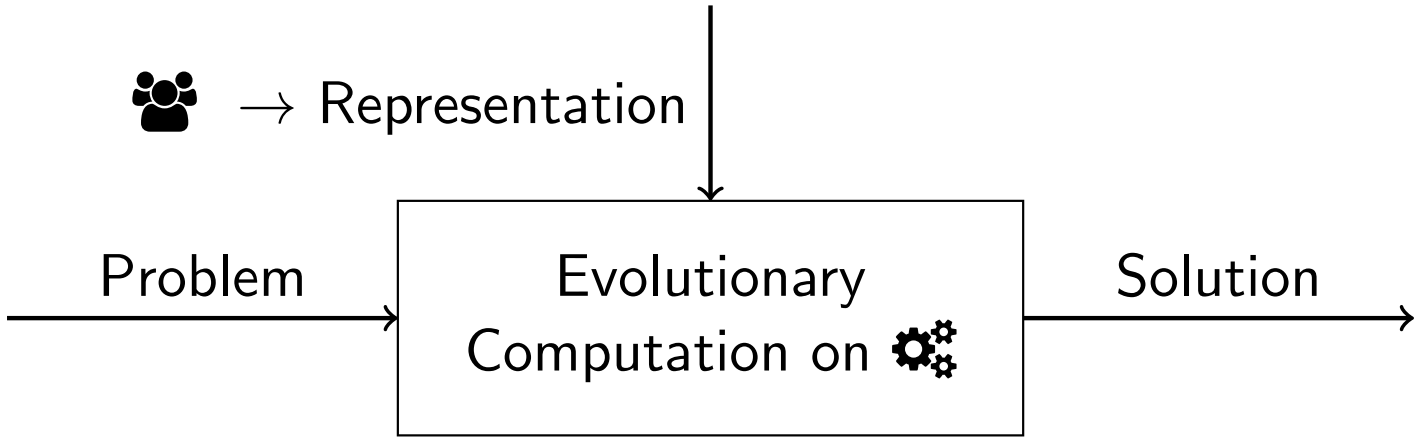
EuroGP, 5/4/2018, Parma (Italy)

What we know

We can use a machine for obtaining automatically a good solution for "any" problem at hand, by means of an Evolutionary Computation.



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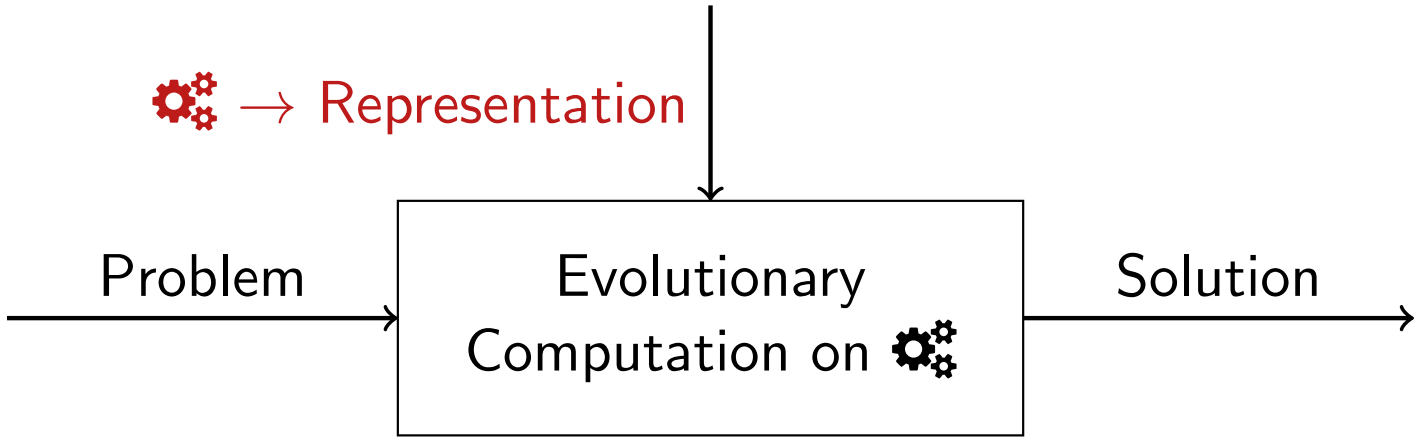

Can we obtain automatically a good representation too?

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Then and now

2007 (30 years perspective): "perhaps the most difficult and least understood area of EA design is that of adapting its internal representation."[1]

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Large debate, many arguments/POVs, weak agreement...

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Choose/design and justify: so far

- How to choose/design?
- How to justify?

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- How to choose/design? $\rightarrow$ inspiration by Nature/guidelines
- How to justify?

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Outcome:

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☺ some agreement on which *properties* matter

- variational inheritance principle

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Idea!

Design automatically the representation
aiming at obtaining good properties

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Sound! Already conjectured and partially attempted:

- "design guidelines [...] may be met not through clever engineering [...], but through the action of the evolutionary process itself" [3]
- meta-evolution, self-adaptation, hyper-heuristic

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We did it for a challenging case: GE!

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Why Grammatical Evolution (GE)?

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- Inspired by Nature
- Challenging, widely studied **indirect representation**

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  - works on any problem with solutions described by a CFG
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- Inspired by Nature
  - (at least loosely)
- Challenging, widely studied **indirect representation**
  - familiar bit string genotype
  - many experimental studies on properties: redundancy, locality, uniformity
  - many representation variants: GE, πGE, HGE/WHGE (and SGE)

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What we need

Problem: evolving a representation with good properties for GE

We need to:

1. define the representation (of grammar-based representations)
2. define the fitness function

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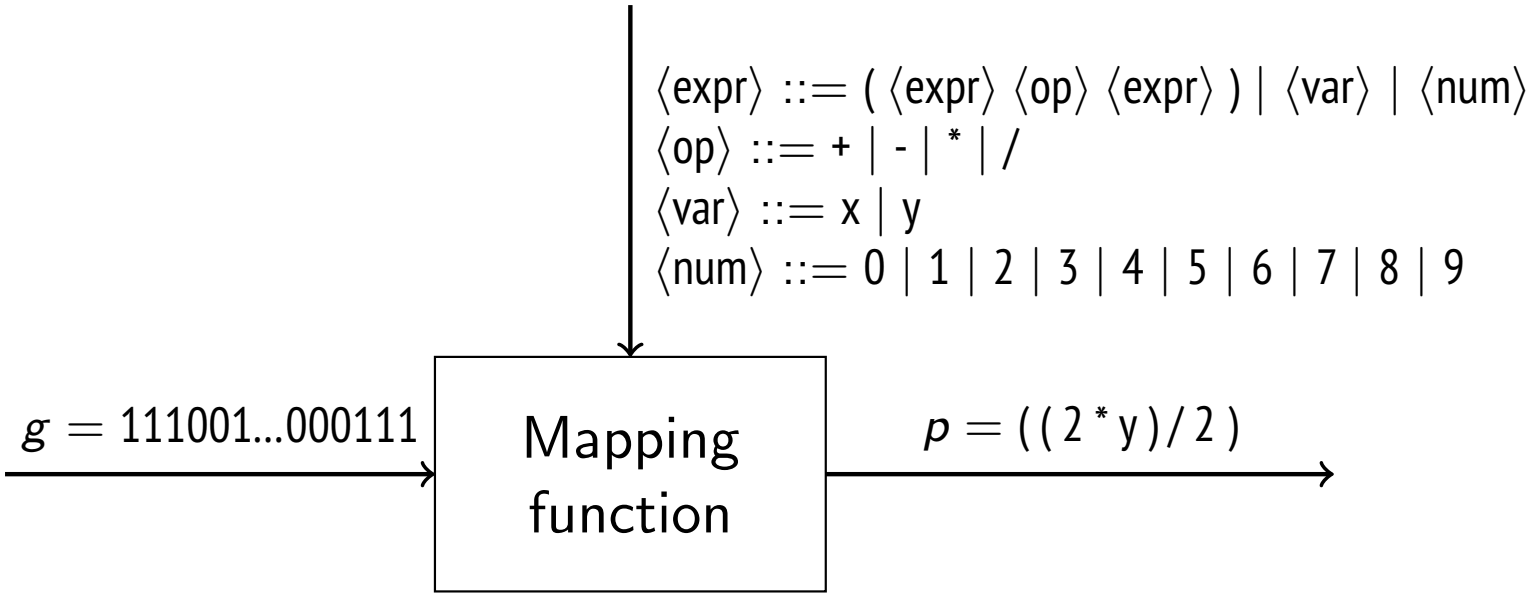
Representation of grammar-based representations

Bit string grammar-based representation, a *mapping function* which:

- maps any bit string to a valid string w.r.t. the user-provided CFG
- in a finite number of steps



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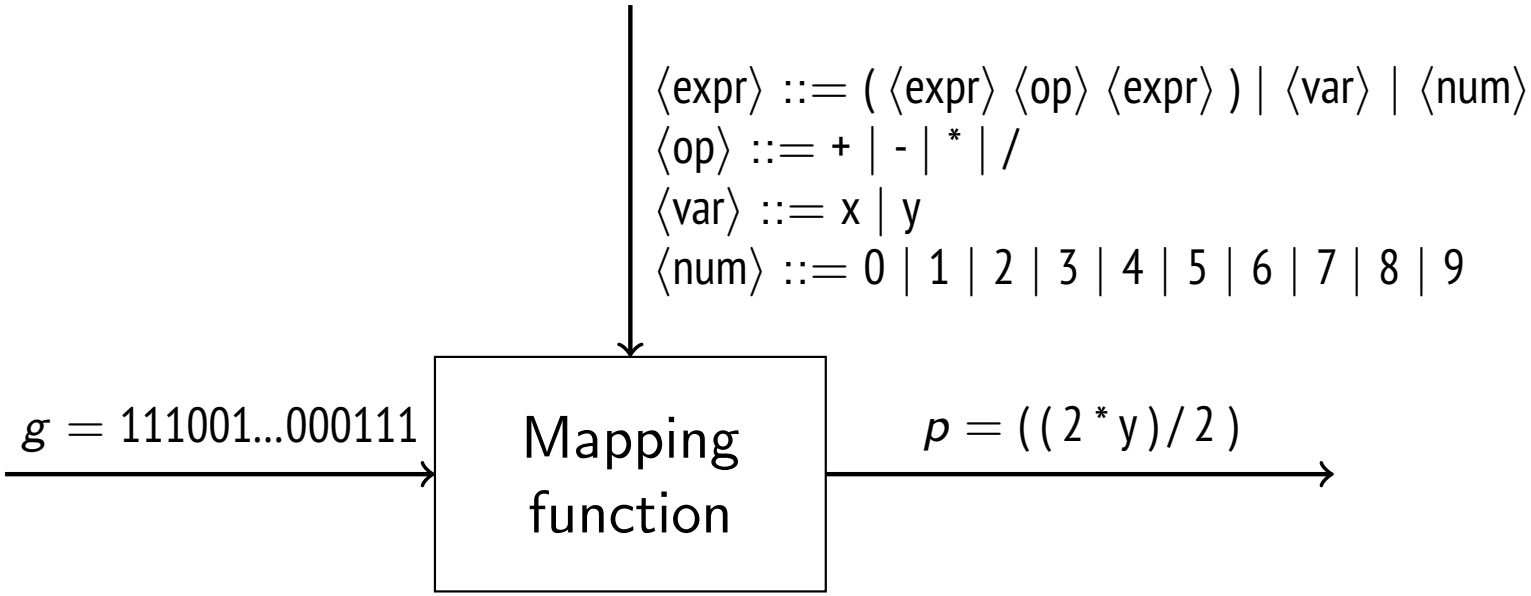
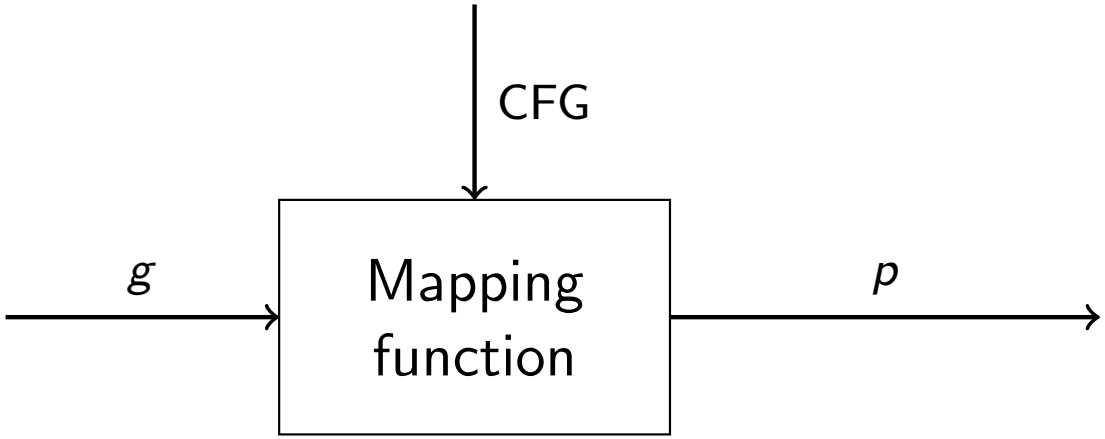


CFGs may be (and usually are) recursive → infinite languages!

Mapping function template



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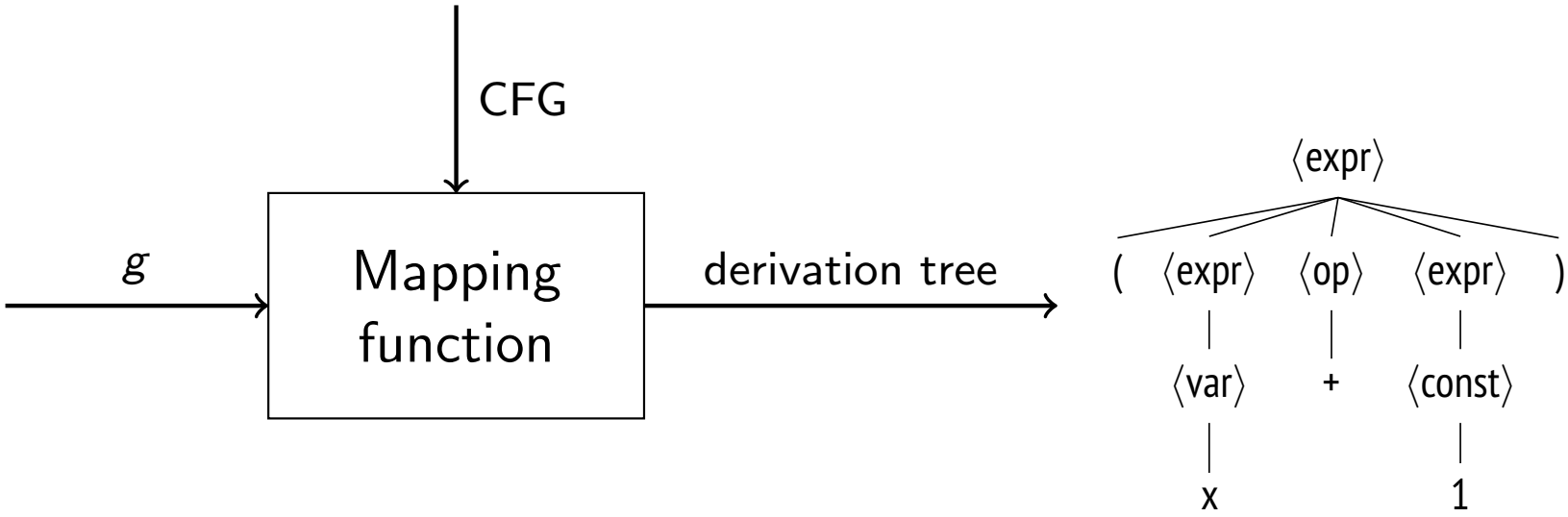
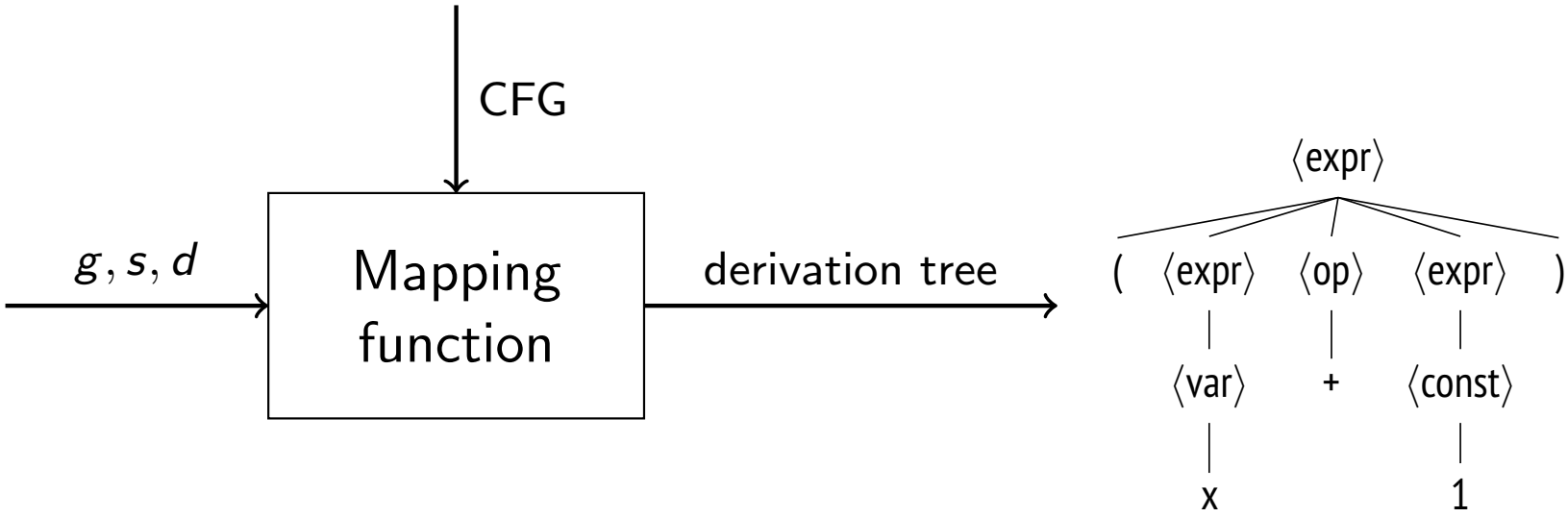


- Returns a derivation tree

Mapping function template



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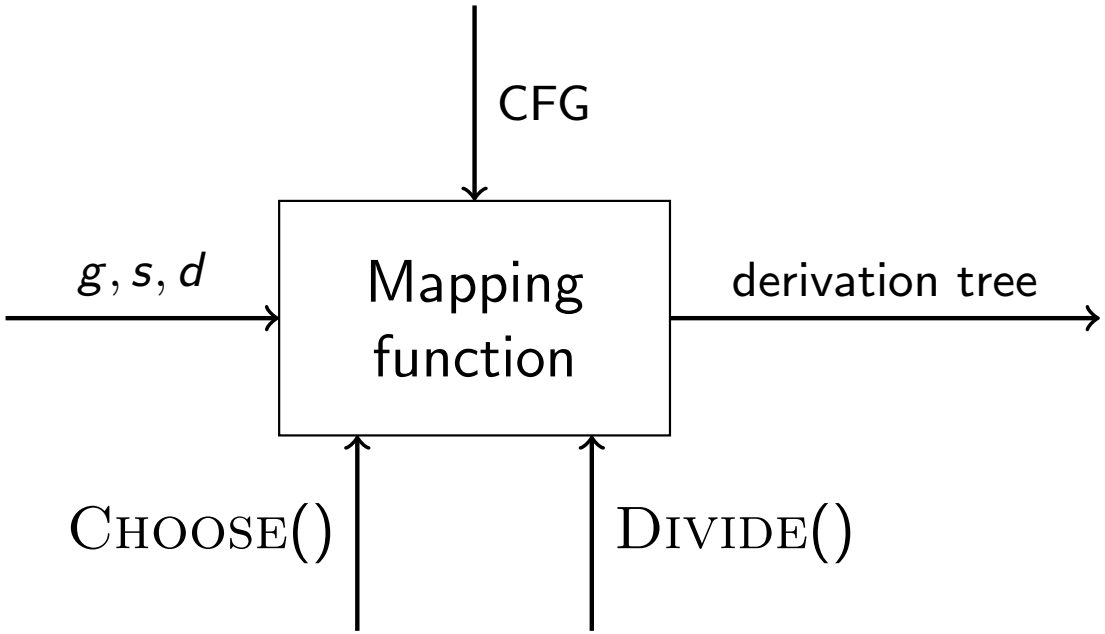

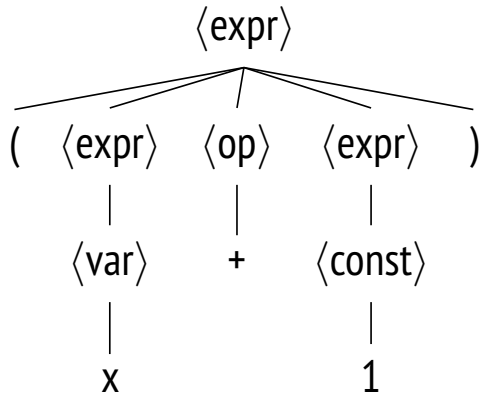

- Returns a derivation tree
- Recursive
- Actual behavior depends on CHOOSE() and DIVIDE()

Mapping function template: details

A recursive $\textsc{Map}(g, s, d)$ function (inspired by WHGE):

1. consider derivation options for symbol s
2. if depth $d > d_{\text{max}}$
   1. choose a predefined option

   else
   1. choose option with $\textsc{Choose}(g, \dots)$
3. "split" g in pieces with $\textsc{Divide}(g, \dots)$
4. for each piece g_i
   1. call $\textsc{Map}(g_i, s_i, d + 1)$
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CHOOSE() and DIVIDE()

A language for the 2 functions, as a CFG:

⟨mapper⟩ ::= ⟨n⟩ ⟨lg⟩

⟨n⟩ ::= ⟨const.n⟩ | ⟨var.n⟩ | ⟨fun.n.g⟩ (⟨g⟩) | ⟨fun.n.n,n⟩ (⟨n⟩ , ⟨n⟩) | ⟨fun.n.ln⟩ (⟨ln⟩) | ⟨fun.n.ln,n⟩ (⟨ln⟩ , ⟨n⟩) | ⟨fun.n.lg⟩ (⟨lg⟩)

⟨ln⟩ ::= ⟨var.ln⟩ | ⟨fun.ln.n⟩ (⟨n⟩) | ⟨fun.ln.n,n⟩ (⟨n⟩ , ⟨n⟩) | apply (⟨fun.n.g⟩ , ⟨lg⟩)

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⟨lg⟩ ::= ⟨fun.lg.g,n⟩ (⟨g⟩ , ⟨n⟩) | ⟨fun.lg.g,ln⟩ (⟨g⟩ , ⟨ln⟩) | apply (⟨fun.g.g,n⟩ , ⟨ln⟩ , ⟨g⟩)

⟨const.n⟩ ::= 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9

⟨var.n⟩ ::= depth | g.count.r | g.count.rw

⟨var.g⟩ ::= g

⟨var.ln⟩ ::= ln

⟨fun.n.g⟩ ::= size | weight | weight.r | int

⟨fun.n.n,n⟩ ::= + | - | * | / | %

⟨fun.n.ln⟩ ::= length | max.index | min.index

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- typed language: numbers ⟨n⟩, lists of numbers ⟨ln⟩, bit strings ⟨g⟩, list of bit strings ⟨lg⟩

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- Map() as a pair of Choose() (⟨n⟩) and Divide() (⟨lg⟩)
- relevant (protected) functions: size, rotate.left, max.index, ...

Expressiveness?

Can express existing human-designed representations!

- standard GE[4]
  - CHOOSE() = int(substring(rotate.left(g, *(gl.count.rw, 8)), 8))
  - DIVIDE() = repeat(g, length(ln))
- HGE (Hierarchical GE)
  - CHOOSE() = max.index(apply(weight.r, split(g, length(ln))))
  - DIVIDE() = split(g, ln)
- WHGE (Weighted HGE)
  - CHOOSE() = max.index(apply(weight.r, split(g, length(ln))))
  - DIVIDE() = split.w(g, ln)

[4] an optimized version with null-invalidity

Bonus

The representation of grammar-based representations is grammar-based! (*meta-GE*)

We can use any grammar-based EA for evolving these representations!

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The representation of grammar-based representations is grammar-based! (*meta-GE*)

We can use any grammar-based EA for evolving these representations!

- we chose CFGGP (thought to be more efficient)
- with a diversity promotion mechanism

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Fitness function

Problem: evolving a representation with good properties for GE

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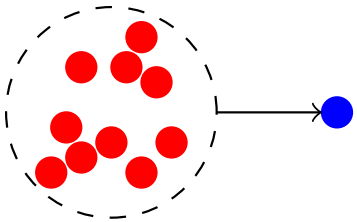

"Known" to be important: the lower, the better

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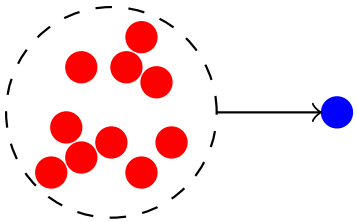

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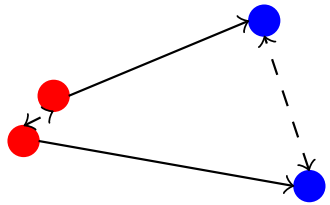

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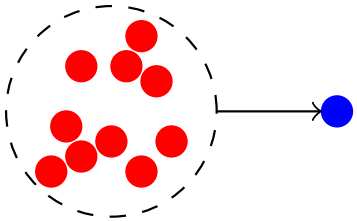

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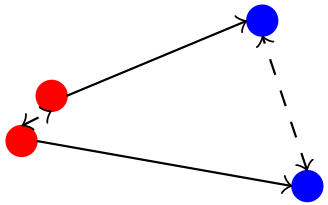
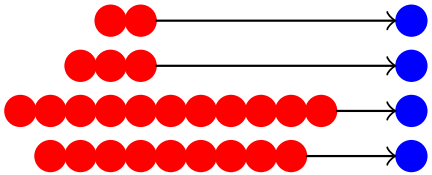


Non-uniformity (NU)



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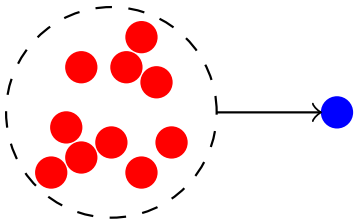

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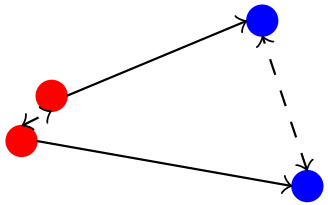

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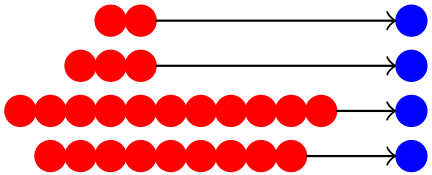

"Known" to be important: the lower, the better

Three variants:

- R (single-objective)
- R/NL (multi-objective)
- R/NL/NU (multi-objective)

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Goals – research questions

RQ1 Can we evolve a representation which is better than the existing ones in terms of redundancy, locality, and uniformity?

RQ2 Are the evolved representations also effective when used inside an actual EA?

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Procedure

1. Learning (tot. 30 runs)
   - fitness (properties R, NL, NU) computed on a symbolic regression CFG (Pagie1) with short genotypes (256 bit)
2. Validation
   - properties R, NL, NU computed on 3 CFGs (Pagie1, K-Landscape, Text) with longer genotypes (1024 bit)
   - search effectiveness on the 3 problems (tot. 2250 runs)
   - comparison against human-designed representations (GE, HGE, WHGE)

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Answers to RQ1

Procedure

1. Learning (tot. 30 runs)
   - fitness (properties R, NL, NU) computed on a symbolic regression CFG (Pagie1) with short genotypes (256 bit)
2. Validation
   - properties R, NL, NU computed on 3 CFGs (Pagie1, K-Landscape, Text) with longer genotypes (1024 bit)
   - search effectiveness on the 3 problems (tot. 2250 runs)
   - comparison against human-designed representations (GE, HGE, WHGE)

Answers to RQ1 and RQ2

RQ1: properties

RQ1 Can we evolve a representation which is better than the existing ones in terms of redundancy, locality, and uniformity?

	Search variant	Redundancy	Non-locality	Non-uniformity
Evolved	R	0.266	0.291	0.284
	R/NL	0.247	0.28	0.292
	R/NL/NU	0.261	0.29	0.288
Human	GE	0.990	1.000	0.000
	HGE	0.620	0.403	2.211
	WHGE	0.410	0.412	2.689

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- yes, we can!
- actual driving properties seem not to matter

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RQ2: search effectiveness

RQ2 Are the evolved representations also effective when used inside an actual EA?

		Final best fitness		
	Search variant	Best	Mean	Worst
KLand.-5	R	0.11	0.6	0.81
	R/NL	0.58	0.66	1
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	GE	1		
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Pagie1	R	3.42	338.66	4488.27
	R/NL	3.32	114.39	1142.28
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	GE	20.99		
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Text	R	6.5	65.12	176
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- best human-designed are better than the average evolved ones
- some evolved are better then the human-designed, on some problems
- representations evolved with R only look better: redundancy is important
  - consistent with literature

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Summarizing

Key findings:

- automatic design of representations of realistic complexity is feasible
- good properties can be achieved!
- $\ldots \not\Rightarrow$ good search effectiveness
  - shed some light on relevance of representation properties

Open issues:

- are R, NL, NU the right properties?
- which part of the property is "in the CFG"?

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Thanks!

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